Wearable ECG-derived Respiration Performance for Respiratory Monitoring with a Non-standard ECG Lead

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Abstract

Continuous cardiorespiratory monitoring is crucial for understanding physiological conditions, particularly respiratory and cardiac diseases. Wearable devices offer an attractive approach for this goal, allowing unobtrusive data collection. This study evaluates two ECG-derived respiration (EDR) algorithms using non-standard electrocardiogram (ECG) leads from a wearable device, and as well as bioimpedance signal for extracting breathing information. The performance is compared against respiratory airflow. 12 healthy volunteers followed a respiratory protocol involving free and paced breathing while ECG, bioimpedance and respiratory airflow were acquired. ECG and bioimpedance were measured using a wearable device, whereas, airflow was recorded using a standard system. Strong linear relationships (Pearson coefficients > 0.90) were observed between EDR signals and respiratory volume, outperforming bioimpedance. The R-wave amplitude algorithm exhibited superior accuracy and lower errors (< 5 %) in respiratory cycle detection. Continuous monitoring remained unaffected over two days. The findings contribute to advancing wearable-based respiratory monitoring techniques for clinical and research applications.

1. Introduction

Cardiorespiratory monitoring is essential for the assessment of respiratory and cardiac diseases. Particularly, continuous monitoring of breathing patterns can provide crucial insights into overall health status [1]. Traditional methods for cardiorespiratory monitoring often involve cumbersome and restrictive equipment, limiting their feasibility for continuous monitoring in real-world settings. To address this issue, the emergence of wearable devices have revolutionized monitoring approaches, offering the potential for continuous unobtrusive monitoring.

The ECG-derived respiration (EDR) and the bioimepdance signals might allow wearable continuous respiratory monitoring. The EDR is based on the electrocardiogram (ECG), which is a physiological signal commonly used for cardiac monitoring. EDR provide a non-invasive and convenient method to assess breathing through algorithms based on the morphological changes that the ECG displays due to the respiratory modulations. Notably, previous studies showed that EDR signals provide excellent estimation of respiratory rate [2–4], making this appealing for continuous respiratory monitoring. Bioimpedance measures the electrical impedance of the biological tissues between the sensing electrodes. Particularly, thoracic bioimpedance can capture breathing information related to respiratory volume, allowing the estimation of breathing parameters [5, 6].

Our study aims to evaluate 2 EDR algorithms as well as bioimpedance for their performance to estimate respiratory rates. Two EDR techniques are included, namely, EDR R-wave amplitude (EDR_R) and EDR R-to-S wave amplitude difference (EDR_{RS}), which are extracted from a nonstandard ECG lead. Through this comprehensive analysis, we seek to provide insights into the performance and suitability of EDR methods and bioimpedance signals to perform wearable continuous monitoring. The protocol involved free and paced breathing since these resting conditions are essential to evaluate their potential in respiratory assessment for clinical and research applications.

2. Material and Methods

2.1. Study protocol and acquisition

The study included 12 healthy volunteers who were recruited from imec, Eindhoven, the Netherlands. The recruitment process was carried out via an email inviting all workers to participate. The study followed the Declaration of Helsinki and all subjects signed a consent form prior

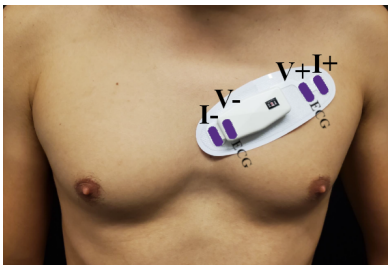

Figure 1: Wearable device used in the study, it was attached to the subjects approximately as depicted above using a patch that incorporates the electrodes: I+ and I- for injecting the current and V+ and V- for voltage measurement which were used for ECG as well.

to participation. The study protocol was reviewed and approved by the ethical committee of imec (IM-NL-SP-2022-0016). It was also reviewed by the Maxima Medical Center Eindhoven (N22.054) to verify that the regulations in the medical research involving human subjects act did not apply to the study.

The protocol consisted of 6 parts (Fig. 2a) and it was performed twice in consecutive days. Each part had a duration of 2 minutes during which the volunteers were instructed to breathe freely and following 3 different respiratory paces: 6, 12, and 15 breaths per minute, as well as simulating apneas. During the protocol, physiological signals were collected: respiratory airflow, ECG and thoracic bioimpedance.

Respiratory airflow was acquired using a standard acquisition system (MP160, Biopac Systems, Inc., Goleta, CA, USA) together with a pneumotach transducer (TSD117, Biopac Systems, Inc.). The transducer was connected to a differential amplifier (DA100C, Biopac Systems, Inc.) to analogically amplify the signal 200 times and to low-pass filter it at cut-off frequency of 300 Hz. The sampling frequency of respiratory airflow was 2 kHz.

For the acquisition of ECG and thoracic bioimpedance we used a custom wearable device (Stichting imec the Netherlands, Eindhoven, the Netherlands). The wearable device was placed on the volunteers' chest, as depicted in Fig. 1. The ECG measurements were continuously obtained using a non-standard single-lead configuration. The bioimpedance measurement was performed using a tetrapolar configuration using a injecting current with amplitude of 48 μA at 40 kHz. ECG and bioimpendance signals were sampled at 128 Hz and 64 Hz, respectively.

2.2. EDR signals and preprocessing

First, all the signals were resampled to 128 Hz. Afterwards, the ECG signals were preprocessed by a high-pass filter to remove the baseline (4^{th} order zero-phase Butterworth, f_c = 0.5 Hz) [7]. R-peaks were detected using an algorithm proposed in [8] and subsequently refined by applying the algorithm described in [2]. Two commonly used

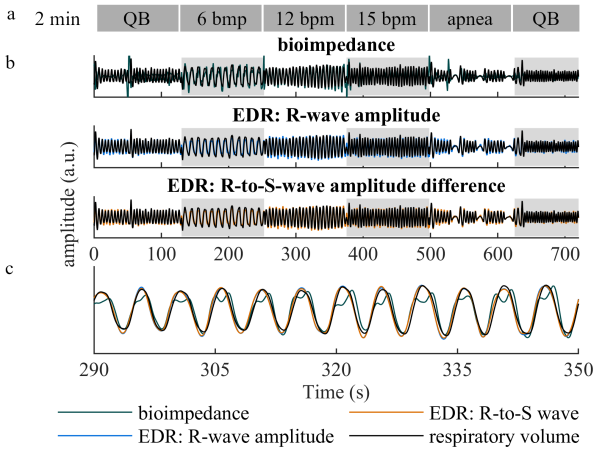

Figure 2: Example of resulting breathing signals during the protocol described in (a). In (b), the 3 signals are compared to the respiratory volume for the entire protocol, whereas (c) displays the comparison for 1-minute segment.

EDR methods were analyzed [4]:

- EDR_R: obtained as the R-wave amplitude
- EDR_{RS}: obtained by the amplitude difference between the R- and S-waves

The EDR signals were resampled to 128 Hz using a cubic spline interpolation.

Respiratory volume was obtained by performing a trapezoidal integration of the respiratory airflow signal.

The EDRs, bioimpedance and volume signals were band-pass filtered: low-pass filter (4^{th} order zero-phase Butterworth, f_c = 1 Hz) and high-pass filter (4^{th} order zero-phase Butterworth, f_c = 0.1 Hz). After filtering, we smoothed the signals by applying a moving average filter of 1-sec window.

2.3. Performance comparison

Respiratory cycle detection: We applied the algorithm we proposed in [9] for detecting the respiratory cycles in the preprocessed EDR and bioimpedance signals.

Signal quality index: We applied the signal quality index proposed in [10] for rejecting bad quality segments. This index was calculated in 32-second windows with 75 % of overlapping for each respiratory signal.

Respiratory rate was estimated from the detection of respiratory cycles using 30-second windows of all the signals signals including the airflow for reference.

The *performance* of each EDR method and bioimpedance was assessed by 3 different measures: correlation, accuracy and errors. The Pearson coefficient was used to evaluate the linear correlation between the EDR and bioimpedance signals with the respiratory volume. The accuracy in the detection of respiratory cycles was calculated by comparing to the reference ones from the airflow signal. Moreover, we calculated the mean average percentage

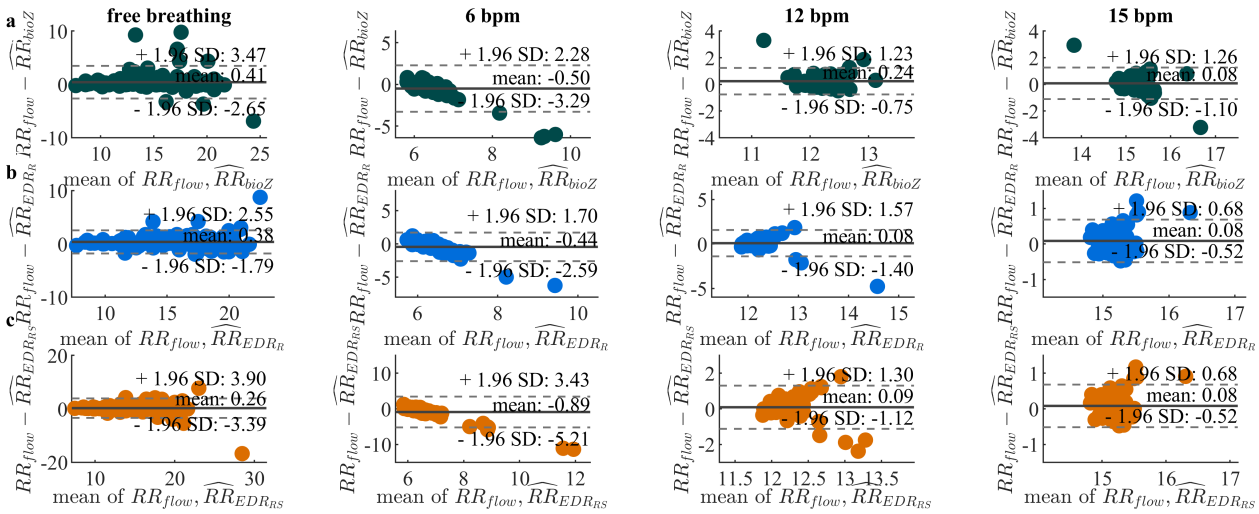

Figure 3: Bland-Altman plots for the estimation of respiratory rate during different parts of the protocol. (a) Using thoracic bioimpedance, (b) EDR R-wave amplitude, and (c) EDR R-to-S wave amplitude difference.

Table 1: Performance of the methods depending on the day of recording

	Pearson correlation			% of data used			accuracy			MAPE (%) RR		
DAY:	1	2	1+2	1	2	1+2	1	2	1+2	1	2	1+2
bioimpedance	0.81	0.75	0.78	90.55	92.75	91.65	0.89	0.90	0.89	3.22	6.12	4.70
EDR_R	0.91	0.90	0.90	96.34	92.70	94.53	0.94	0.92	0.93	4.24	4.62	4.42
EDR_{RS}	0.91	0.90	0.90	94.86	94.75	94.80	0.91	0.92	0.91	5.98	6.37	6.18

MAPE: mean average percentage error, RR: respiratory rate.

error (MAPE) between the respiratory rate (RR) estimation and the reference estimation as well as Bland-Altman plots to evaluate the disagreement between the respiratory rates estimation as well as trends on the differences between measurements.

3. Results

A total of 12 healthy volunteers initially participated in the study. However, the data of 2 volunteers were rejected from the analysis due to an adverse event and a low ECG quality. The remaining volunteers comprised 6 females and 4 males. Their age was 35.4 $\pm$ 9.3 years, and their mean body mass index was 21.9 $\pm$ 1.7 kg/m^2.

The main objective of this study was to assess and compare the performance of two EDR methods, using non-standard ECG leads, as well as the bioimpedance signals to detect respiratory cycles and estimate RR. The respiratory airflow was used as reference which RR values were, calculated as median (1^{st} - 3^{rd} quartile), 15.89 (13.63 - 18.13) bpm for the free breathing (QB), 6.20 (6.05 - 6.31) bpm for the 6 bpm paced breathing part, 12.19 (12.04 - 12.43) bpm for the 12 bpm part and 15.10 (15.04 - 15.33) bpm for the 15 bpm part.

An example of the preprocessed breathing signals used in this study is illustrated in Fig. 2 including the 6 protocol parts. We computed the well-established Pearson correlation coefficient using the signals without considering the results of the SQI. The coefficients were higher than 0.75 for all 3 signals evaluated in the study. Specifically, the EDRs exhibited an excellent correlation coefficient of $>$ 0.90.

The evaluation of the EDR signals in terms of accuracy and errors involved excluding the bad quality segments identified by the SQI and the parts where the subjects simulated apneas. Note that after excluding data using the SQI, less than 10 % of the data was removed. The accuracy of respiratory cycle detection was higher than 0.89, with a slightly better performance observed for the EDR signals (Table 1). The MAPE values for the estimation of RR were all lower than 6.18 %. The EDR_{RS} showed the worst performance compared to EDR_R and bioimpedance signals which had errors below 4.5 %. Furthermore, the performance metrics for the EDR signals and bioimpedance were consistently similar on the 2 consecutive days.

4. Discussion

In this study, two EDR signals, EDR_R and EDR_{RS}, as well as bioimpedance signal obtained from a wearable device were compared for their performance on the estimation of respiratory rate using respiratory airflow as reference. The EDR_R algorithm demonstrated superior performance in terms of respiratory cycle detection accuracy and

error metrics. Bioimpedance and the EDR_{RS} algorithm performed slightly worse.

In terms of linear relationship, all evaluated methods demonstrated moderate to strong correlation to the respiratory volume. The EDR signals exhibited excellent linearity, with coefficients higher than 0.90. However, we observed a lower correlation for bioimpedance (0.78) compared to previous studies [5], potentially due to more segments being identified as bad quality by the SQI (Table 1). This discrepancy might be attributed to differences in wearable devices, protocols, and specifically, the area of measurement. The bioimpedance measurement, as depicted in Fig. 1, primarily captured impedance changes related to the left side, which might have influence in the correlation results. Despite these limitations, the agreement between signals, as shown in Fig. 2, is excellent.

The accuracy in respiratory cycle detection aligns with previous studies [9] for the three signals. Thus, the similarities in signal morphology and performance suggest that this algorithm is suitable for EDR signals.

The EDR_R exhibited the lowest error values, remaining below 5 % for both days of measurements. Our findings differ from previous studies that found a more robust performance for the EDR_{RS} algorithm [4, 11]. Future investigations should assess if these differences are due to the use of non-standard ECG leads, warranting a direct comparison. Nevertheless, our error values are slightly higher than those reported in [4, 12], 4.42 % versus 3.8 % and 2.26 % respectively, probably due to the differences in the methods used for RR estimation.

Bioimpedance performance was excellent as it was for the EDR_R, in terms of accuracy and errors. The bioimpedance errors were the lowest during the 1_{st} day, but using less data due to the SQI rejection. The performance of the 3 methods remained consistent regardless of the measurement day (Table 1). This indicates that continuous monitoring using the wearable device did not affect the breathing estimation for EDR or bioimpedance.

Overall, this study highlights the potential of EDR signals for continuous cardiorespiratory monitoring and underscores the importance of non-standard ECG leads in respiratory assessment. The study confirms that the algorithm proposed for bioimpedance signal is suitable for the EDR signals, showing similar performance in the 3 signals under study. The positive results reinforce the utility of wearable devices for cardiorespiratory monitoring. Future studies should explore the use of this ECG measurement for extracting respiratory information in longer recordings.

Acknowledgments

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